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Farmers' willingness to accept payments for ecosystem services on agricultural land: The case of climate-smart agroforestry in Ethiopia

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ABSTRACT

This study examines smallholder farmers' preferences for the uptake of contractual climate-smart agroforestry, which yields economic and ecosystem benefits. A discrete choice experiment was conducted with smallholder farmers in Ethiopia to elicit their willingness to participate in a payment for ecosystem services (PES) scheme that incentivizes integrating *faidherbia albida* (a fertilizer tree) in their mono-cropping farming system. Attributes evaluated are "number of planted trees", "payment amount", "payment type", and "contract period". The presence of heterogeneity in the choice behavior of farmers warrants the use of the generalized multinomial logit and latent class conditional logit models to allow for farmer- and class-specific preferences, respectively. The results show that farmers derive higher utility from up-front payments. Farmers also strongly prefer food as the mode of payment than cash. Moreover, low numbers of mandatory planted trees and short-term contracts are found to be essential attributes that positively affect farmers' decisions to take-up a contractual arrangement to grow trees on their agricultural land. Our analysis also shows the presence of heterogeneity in preferences across segments of farmers in conjunction with differences in household characteristics. These findings shed light on the considerations that must be accounted for when designing and implementing environmental policies such as PES schemes that promote large-scale adoption of climate-smart agroforestry, which would transform smallholder agriculture into a sustainable farming system.

1. Introduction

Climate-smart agriculture (CSA) offers innovative possibilities for developing countries not only to buffer their agricultural production from the effects of climate shocks but also to orient agriculture as part of the solution to the climate change challenge (Campbell et al., 2014). The term CSA refers to a set of agricultural practices that can increase resilience to weather extremes through its "triple wins" of sustainably increasing agricultural productivity and incomes, adapting to climate change, and removing or reducing greenhouse gas emissions (FAO, 2010). Climate-smart agroforestry is one such practice which involves the integration of *faidherbia albida* (a fertilizer tree) into food crop systems (Akinnifesi et al., 2010; Garrity et al., 2010; Sida et al., 2018; Thierfelder et al., 2018). The practice comprises benefits associated with yield increments, and ecosystem services such as; mitigating greenhouse gas emissions, protecting biodiversity, and reducing land degradation.

Climate-smart agroforestry improves soil structure and fertility, increases cereal production by 50–400 percent, reduces production costs by replacing around 75 percent of mineral fertilizers (Akinnifesi et al., 2010), and sequesters up to 4 tons of carbon per hectare per year (Mbow et al., 2014). Despite its economic and ecosystem benefits, the uptake of climate-smart agroforestry by smallholder farmers in sub-Saharan Africa (SSA) remains far less than optimal (Garrity et al., 2010; Glover et al., 2012). In the short run, tree planting in agricultural land involves making expenditures to maintain the trees without yield and financial returns as the production cycle is long. As a result, short-term income losses often inhibit farming households from investing in climate-smart practices which generate long-term economic and environmental returns (Ndah et al., 2014; Neufeldt et al., 2011).

The standard policy intervention in the face of positive environmental spillovers is to introduce incentives so that private individuals benefit from the use of environmentally responsible practices (Martin et al., 2014; Reed et al., 2015). Researchers and policymakers alike have advocated payments for ecosystem services (PES) as an incentive-based approach to internalizing the positive externalities of land use decisions. The conceptualization of PES is based on creating markets for trading ecosystem services, and correcting market failures that lead to

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their undersupply (Muradian et al., 2010). In a pure market-based PES, the primary concern is the improvement of environmental outcomes and not necessarily equity (Adhikari and Agrawal, 2013; Pagiola et al., 2005). Hence, such PES programs are more suitable for well-off farmers with well-defined property rights, low transaction costs, and better resource endowment (Bremer et al., 2014; Lansing, 2017; Sierra and Russman, 2006).

However, the poor and vulnerable farming households should be targeted as their inclusion will ensure sustainable land use and the Pareto-efficient provision of ecosystem services (Börner et al., 2017; Reed et al., 2015). If payments are set to reflect opportunity costs for ecosystem service providers, poor households, who have lower opportunity costs in absolute terms, would be the main beneficiaries of PES schemes (Muradian et al., 2010). Hence, the design and implementation of sustainable PES schemes that benefit the poor and vulnerable farming households should be guided by both efficiency and equity objectives (Leimona et al., 2015). To that end, the first step should involve understanding which attributes of a PES scheme influence the participation of poor farmers in the program. Eliciting farmers' stated preferences would uncover how they value the attributes of a proposed PES contract before launching the program. So far, a considerable amount of studies that elicit stated preferences have been conducted to understand the various natural, social and economic factors that determine participation in conservation- and restoration-oriented ecosystem service provision mainly via land retirement (i.e. the land should not be primarily used for farming activities).[1]

In the context of SSA, the exclusive planting of trees on private agricultural lands contradicts with the region's policy agenda which aim to increase agricultural production to feed the growing population. Climate-smart agroforestry could solve this policy dilemma by integrating the welfare and ecosystem concerns on smallholders' agricultural land. However, few studies provide empirical evidence on the willingness of smallholder farmers to intercrop trees which generate multiple benefits for food security and the ecosystem. Notable examples are the work by Porras (2010) who found that the number of smallholder contracts has increased as a result of including agroforestry as a category in PES schemes in Costa Rica. Jack (2010) also assessed alternative market-based instruments for the efficient allocation of tree planting contracts on the private lands of smallholder farmers in Malawi. Cranford and Mourato (2014) used a discrete choice experiment (DCE) to examine farmers' preferences for a reduction in the cost of credit as a mode of payment for practicing agroforestry in Ecuador.

This paper examines farmers' willingness to accept payments for planting fertilizer trees on their agricultural land in Ethiopia. Although the above-mentioned studies consider the eligibility of agroforestry under PES financing mechanisms, as any conventional PES program, the payment is ultimately attached to forest cover as a tradable ecosystem service. Put differently, farmers need to have the tradable commodity – grown up trees on their farm plots – before claiming incentives for their services to the environment. This study departs from the previous approach in that the hypothetical PES program rewards farmers for adopting climate-smart agroforestry from the initial year of planting the tree seedlings. Under this design, poor farmers can bear the short-term costs associated with their investment in the practice. Hence, this paper is a novel attempt at integrating efficiency and equity concerns in a PES scheme that accommodates agroforestry in the context of smallholder agriculture in SSA. A DCE is used to elicit farmers' preferences toward a PES program that would make annual payments as compensation for the direct and opportunity costs of investing in climate-smart agroforestry. In addition to the payment amount, the study also evaluates the relative importance of three additional attributes: required number of planted trees on the farm plots, payment type (cash or food), and contract period in years. The study also examines the socioeconomic factors that influence households' decision to accept the contractual tree planting arrangement or remain with their current monocropping practice (the status quo).

We utilized a generalized multinomial logit (G-MNL) and latent class conditional logit (LCL) models to examine variations in the choice behavior of individuals and classes of farmers, respectively. The G-MNL model accounts for both individual-specific scale and preference heterogeneity. All the G-MNL parameter estimates for the attributes considered in the PES program are statistically significant, an indication of the relevance of the chosen attributes. We find that farmers derive higher utility from up-front payments. Farmers are willing to receive a low amount if the mode of payment is food rather than cash. Moreover, low numbers of mandatory planted trees and short-term contract periods significantly motivated the take up of contractual agroforestry. We also find that farmers with a larger landholding and those who own a television or radio have stronger preferences for the PES contract than the status quo. The results from LCL model also show the presence of heterogeneity in preferences across segments of farmers in conjunction with differences in household characteristics. These findings provide policy-relevant information on the design considerations that must be taken into account for implementing PES contracts that promote adoption of climate-smart agroforestry among farmers in SSA and particularly in Ethiopia.

The remainder of the paper is organized as follows. Section 2 describes the relevance of climate-smart agroforestry in the context of Ethiopia's development strategy. Section 3 provides a theoretical framework that links the concepts of climate-smart agroforestry and PES. Section 4 presents the source of data and data analysis techniques. Section 5 and section 6 present the results and discussion of the study, respectively. Section 7 concludes the paper.

2. Climate-smart agroforestry in the context of Ethiopia

Ethiopia has given top priority to the agricultural sector as the basis for economic growth. However, the sector's sensitivity to the vagaries of weather and at the same time its contribution to climate change has caused a major concern. Out of the total (150 Mt CO2e) national greenhouse gas (GHG) emissions in 2010, 50% came from the production of agricultural output and around 20% are driven by deforestation for agricultural land (FDRE, 2011). Furthermore, the agriculture sector would add around 110 Mt CO2e in GHG emissions by 2030 if Ethiopia pursues a conventional development path (ibid). The conventional agricultural development path mainly involves the use of additional natural and physical resources for intensifying agricultural production, which would increase the carbon footprint as it has been observed in other parts of the world.

Shifting away from the conventional path, Ethiopia has devised a Climate Resilient Green Economy (CRGE) strategy that aims at overcoming the challenges of developing a green economy. The CRGE strategy is a blueprint to unleash Ethiopia's potential for a sustainable model of growth. Out of the four pillars that will support the strategy, two of them are related to agriculture: (i) adoption of land productivity- and efficiency-enhancing measures and (ii) increasing GHG sequestration in trees (i.e., planting trees for their economic and ecosystem services). Therefore, the strategy attempts to orient agriculture in a manner not only to significantly cut the contribution of the sector to the national GHG emissions but also to use agricultural soils as a sink for the emissions emanated from other sectors such as manufacturing and transportation.

To that end, agroforestry offers a possibility for abatement of GHG emissions by providing the greatest soil and above ground carbon sequestration in tropical areas (Feliciano et al., 2018). The Agricultural Extension Directorate of Ethiopia has given due emphasis for large-scale promotion and adoption of *faidherbia albida* in the country. As part of

[1] See Whittington and Pagiola (2012) for a review on the application of stated preference methods for PES studies, and the stated preference-based PES studies listed under a meta-analysis by Hjerpe et al. (2015).

the activities outlined in the CRGE Strategy, in 2011, Ethiopia launched a national program to plant over 100 million *faidherbia albida* trees in the agricultural lands of smallholder farmers (Jirata et al., 2016). The agroforestry practice using *faidherbia albida* has been promoted to address issues of soil fertility, carbon sequestration, and resilience to climate variability. Integrating *faidherbia albida* trees in agricultural lands in Ethiopia has been documented to improve soil water retention, nitrogen and phosphorus use efficiencies, and green cover during the off-season (Sida et al., 2018). Despite Ethiopia's ambitious output-based target to reap the benefits from the large-scale adoption of climate-smart agroforestry, it has not been clear how to facilitate farmers' medium to long-term investment on the practice to realize the target.

3. Theoretical framework

Poor households that are at the bare minimum in their current consumption cannot afford any decline in their current subsistence income, and hence find it hard to invest on agricultural innovations that do not provide immediate cash reward (Neufeldt et al., 2011). In the spirit of the reference-dependent utility model of Köszegi and Rabin (2006), the lack of uptake of agroforestry by smallholder farmers could be explained by the overemphasis farmers give to the loss in utility as a result of a decline in their reference (i.e. status quo) consumption level. Based on that, the short-term overall utility is given by $u(e|r) = m(e) + n(e|r)$, where $m(e)$ is the short-term consumption utility derived from planting *faidherbia albida* trees, and it is hardly different from zero. Whereas, $n(e|r)$ is the short-term utility loss due to climate-smart agroforestry, and it is determined by considering the foregone reference (status-quo) consumption level.

If a PES program compensates farmers for the direct and opportunity costs of investing in tree planting on their agricultural land, the disutility to farmers may be avoided and leave them indifferent between the status quo (i.e. mono-cropping) and adoption of climate-smart agroforestry. Therefore, it is an imperative theoretical and empirical inquiry to estimate farmers' willingness to accept compensations for short-term private losses emanating from conservation or restoration-oriented land use decisions such as adopting climate-smart agroforestry. To this end, we present a model of farmers' willingness to participate in a PES contract based on the agricultural household model that is shown in Singh et al. (1986); de Janvry et al. (1991); and Taylor and Adelman (2003).

3.1. Households' utility maximizing consumption function

Due to market imperfections, quasi-universal circumstances in developing countries, farm households often act as a consuming (utility maximizing) and producing (profit maximizing) agents as a result of the non-separability between consumption and production decisions (Singh et al., 1986). Farm households strive to maximize utility from consumption of home-produced goods, marketed goods, and leisure. Agricultural goods are produced through farm technology represented by a production function.

$$Q = Q(L, O, \bar{R}) \tag{1}$$

where$L = \bar{T} - l_c$ is the labor used for the production of agricultural outputs given as the difference between the total time endowment ($\bar{T}$) and labor consumed for leisure (l_c). O is a vector of other variable inputs such as mineral fertilizers. $\bar{R}$ is land endowment which is assumed to be fixed in the short-run. If the household is entirely subsistence, what is produced is entirely consumed ($C_f = Q$). But usually farming households in developing countries are semi-commercialized as they sell marketable surplus M ($M = Q - C_f$): the households are net sellers if $M > 0$ and net buyers if $M < 0$. In this scenario, for farming households operating in a mono-cropping system, profits from agricultural production can be derived as:i

$$\pi = p_y M - wL - p_o O \tag{2}$$

where π is profit in the mono-cropping system, p_y is the output price. The general price level has a positive (negative) effect on the profit of the net seller (net buyer) households. ***w*** is wage rate and p_o is a vector of prices of the other variable inputs. Consequently, the utility maximizing consumption level at the status quo – without agroforestry – is determined by:

$$C^* = C(C_f, \pi) \tag{3}$$

The introduction of agroforestry involves streams of added costs and reduced returns that affect the households' profit and ultimately their utility maximizing consumption. The profit in the case of agroforestry would be:

$$\pi_e = \pi - I \tag{4}$$

where π_e is profit in agroforestry, I is the present value of the total investment expenditure on agroforestry and it can be extended as:

$$I = (wl_e + \bar{E} + p_y Q_g)(1 + r)^{1-t} \tag{5}$$

where l_e is the labor utilized for agroforestry; $\bar{E}$ is expenditures on materials and equipment; $Q_g = Q(\bar{F})$ is foregone food crop production as a result of land taken away by agroforestry where $\bar{F}$ is number of planted trees; ***r*** is time preference (discount factor); ***t*** is number of years households are making expenditures on climate-smart agroforestry before getting positive economic gain attributable to the practice. Analogous to Eq. (3), in the short-run, the utility maximizing consumption in the climate-smart agroforestry system is:

$$C_e^* = C(C_f, \pi_e) \tag{6}$$

3.2. Modeling WTA and participation in PES contract

The measure of farmers' willingness to accept (WTA) compensation for renouncing their status quo utility maximizing consumption can be computed in Eq. (7) as:

$$\mathrm{WTA} = [C^* = C(C_f, \pi)] - [C_e^* = C(C_f, \pi_e)] = I \tag{7}$$

The farmer is assumed to participate in the PES contract only if the contract payment offer is greater than or equal to WTA. Moreover, the design considerations for PES schemes go beyond the amount of payment, which is a function of output price, wage, and discount factor. Eq. (5) shows that WTA (i.e, I) is also a function of the number of trees planted in the farm, and time (number of years that expenditures are made before realizing financial benefits). Since farm investment decisions are determined by consumption and production characteristics, WTA is also very likely to be affected by variables that affect production and consumption preferences. Therefore, farmers' willingness to participate in PES contracts (or accept compensation for foregoing the status quo) and their preferences for climate-smart agroforestry will be a function of household characteristics. For instance, access to available information influences an individual's knowledge, attitude, and perception, which are the main drivers of choice decision (Aryal et al., 2009). Moreover, farm income and wealth of the household are also the major determinants of the households' willingness to participate in PES programs (Katrina and Andreas, 2012; Li et al., 2017) and risk and time preferences (Tanaka et al., 2010). The following generalized model, which leads to our empirical model specification in Section 4.3, presents farmers' willingness to participate in a PES program that rewards climate-smart agroforestry.

$$V_i = \alpha + \beta X_i + \gamma Z_i + \varepsilon_i \tag{8}$$

whereV_i is the probability that the ith ($i = 1, 2, \ldots, n$) household will participate in the PES contract (intercrop fertilizer trees) given a vector of PES attributes (X). Z is a vector of farm and farmer characteristics that are important determinants of preferences and ε_i is the random term. α, α and γ are parameters to be estimated using the appropriate choice analysis technique.

4. Methodology

4.1. Description of the study area

The study was conducted in Hintalo Wajirat district which is one of the 34 rural districts of Tigray regional state in Northern Ethiopia (Appendix Fig. 1). The study district is located South-East of Mekele, the capital city of Tigray region, with GPS coordinates 13° 09′ 60.00″ N and 39° 39′ 59.99″ E. The district has a total area of 193,309 hectares of land and with an estimated total population of 170,243, out of which, 50.8 percent are females (CSA, 2013). Rainfed mixed crop-livestock farming is the primary source of livelihood in the district. Extreme environmental degradations in terms of soil erosion, loss of general biodiversity, and desertification have occurred throughout the district. In the past two decades, community-based conservation programs have played a significant role in mobilizing human and financial resources towards the construction of stone terraces, reforestation efforts, and enforcement of grazing restrictions (Birhane et al., 2017). The current policy priority of Tigray region in general and Hintalo-Wajirat district in particular is to showcase for large-scale adoption of *fadehrbia albida* which has been identified as a thriving agricultural innovation to enhance households' food security and reduce their vulnerability to the effects of climate change (Noulekoun et al., 2017; Rinaudo, 2010).

4.2. Source of data and method of data collection

Hintalo Wajirat district has a total of 22 *tabias* (*kebeles*),[2] which we could not cover them all in our survey due to financial and time constraints. We randomly selected seven *tabias* (Appendix Fig. 1) and conducted a stated preference survey using a structured questionnaire to administer face-to-face interviews, from January to mid-February 2017, with 200 randomly selected smallholder farmers. Our structured questionnaire has sections to collect data on characteristics of the household head, demographic and socioeconomic variables of the household, and non-incentivized discrete choices on the adoption of contractual climate-smart agroforestry. We recruited enumerators from outside the study district and held a training session to build their understanding of the contents of the stated preference survey questionnaire. Stated preference methods uncover how individuals value different "alternatives" (whether goods, services, or courses of action) in a survey context (Louviere et al., 2010). In contrast to revealed preference methods using real-world data, stated preference studies are a standard tool for assessing people's preferences in hypothetical situations that do not currently exist, for instance before implementing a new PES program.

Contingent valuation method (CVM) and discrete choice experiment (DCE) are the two widely used approaches to elicit stated preferences from individuals. The CVM is an interview technique where people are asked to estimate the value they attach to certain alternatives directly. As long as the respondents are convinced that their responses will be used to help inform policy actions, the standard economic model suggests that economic agents will respond to the survey expecting to maximize their welfare (Carson, 2012). On the other hand, in DCE, respondents make choices between cleverly designed alternatives to estimate the weights that they place on each of the attributes that define the alternatives (Greiner et al., 2014). DCE has a sound theoretical foundation in random utility theory, which hypothesized that individuals are rational decision makers maximizing utility relative to their choices (McFadden, 1974).

The most common problems in stated preference methods are hypothetical and strategic biases. In the former case, what people actually do might not be the same as what they initially said they will do. Or, in the case of the latter, they might deliberately overstate or understate their true preferences to influence policy decisions that come out of the study. To minimize the hypothetical and strategic biases which are highly prevalent under the open-ended willingness to accept questions of CVM (Adamowicz et al., 1998), this study employed DCE. Moreover, "cheap talk" scripts have been common features of stated preference studies to minimize biased responses (Carlsson et al., 2005; Cummings and Taylor, 1999; Tonsor and Shupp, 2011). Accordingly, while showing all sample farmers photos of climate-smart agroforestry that are depicted in Appendix Fig. 2, a "cheap talk" script (presented under the figure) was read to enlighten them about the choices that they are requested to make and facilitate honest responses.

4.3. Design of the discrete choice experiment

The DCE design is generated following many sequential steps. The first step involves the decisions related to the selection of attributes, and attribute levels (Greiner et al., 2014). The attributes and their levels are determined based on the literature on agroforestry, and consultations with agricultural extension and natural resource management experts in the study area. Except for the attribute levels of the "payment amount", the other attributes along with their levels are identified based on the existing literature on PES and agroforestry. For optimal climate-smart agroforestry, the common practice is planting one hundred *faidherbia albida* tree seedlings per hectare with spacing at 10×10 m (Fagg, 1995) and can be thinned down to 20–30 trees per hectare as the trees fully mature (Kang and Akinnifesi, 2000).

The "contract period" has levels that reflect the number of years farmers receive payments from the PES program. The levels are set based on the number of years farmers may wait before realizing positive net returns from their investments on climate-smart agroforestry. According to Baumer (1983), it will take at least 3–5 years after planting to see early signs of improvements in crop productivity that could be attributed to the presence of *faidherbia albida* trees in the farm plots. In most usual cases, it might take 10 years and above before farmers exploit the full economic benefits from climate-smart agroforestry (Akinnifesi et al., 2010). The classification of the "payment type" into cash or food is based on the argument that in the absence of complete product markets, under which poor smallholder farmers usually operate, the two modes of payments are distinct since one cannot readily be converted to the other (Currie and Gahvari, 2008).

Setting the levels for the "payment amount" requires the consideration of the direct and opportunity costs of climate-smart agroforestry. To this end, we conducted a private interview and field visits with 12 (6 crop production and 6 natural resource management) experts in the study area to identify the added financial costs and the reduced financial gains associated with planting 100 *faidherbia albida* trees per hectare on the lands of smallholder farmers. The direct costs include annual hired labor cost for planting and managing the trees in farm plots, costs for fencing the seedlings to avoid damage by humans or animals, and cost for the purchase of a pruning tool to remove damaged branches to protect the well-being of the trees.

We also considered the loss in farm income (the opportunity cost) due to planting trees on agricultural land. The experts estimated the area that 100 grown up *faidherbia albida* trees aging 10 years would take – which is the area of the trunk size. Based on each expert's response, we then calculated the income loss to farmers as a result of giving up the area that would have specifically been utilized for the production of wheat, which is predominantly grown in the study area. Therefore, the levels of the "payment amount" are non-conservative estimates, and determined considering four scenarios of the responses of the experts; (i) the minimum income loss estimate (ii) the median income loss estimates (iii) the mean income loss estimates, and (iv) the

[2] *Tabia* (*kebele*), which comprises villages, is the smallest administrative unit in Ethiopian federal government structure.

Table 1
Description of the attributes and attribute levels.

Attributes	Description and coding of the attributes	Attribute levels
Number of planted trees	The number of required *faidherbia albida* trees per *timad* that need to be planted in the farm plots.	5, 10, 20, 25
Payment amount	The annual payment in Ethiopian Birr (ETB).[a] The amount of payment considers the additional financial costs and the reduced financial gains per *timad* associated with planting *faidherbia albida* trees in the farmers' plots.	125, 135, 155, 190
Payment type	A dummy variable for the payment type taking the value of 1 for food and 0 for cash. During the survey, the cash equivalent quantities of wheat in kg are presented in the choice tasks.	Cash, Food
Contract period	The total number of years farmers will be incentivized based on the number of existing *faidherbia albida* trees on their farm plots.	3, 5, 10

Note: [a] 1 ETB is 0.044 U.S. Dollar (USD) based on the survey period average official exchange rate, which is obtained from OANDA currency converter (http://www.oanda.com/currency/converter).

maximum income loss estimate. Table 1 presents the description and coding of the attributes, and the levels attached to each attribute. The attribute levels for the "payment amount" and "number of planted trees" are converted on the basis of *timad*[3] (local land area unit measure).

Once the attributes and their levels have been determined, the second step is to combine them into alternatives which ultimately form the complete choice sets. The number of possible combinations of attribute levels, which is called the full factorial design, is very large ($4 \times 4 \times 2 \times 3 = 96$). These can be combined into 4560 pairs of alternatives [$(96 \times 95)/2 = 4560$], which is too many to be practically feasible. Hence, the final fundamental step is combining the attribute levels into alternatives and choice sets in such a way so as to design a good DCE. A good DCE design is one that facilitates precision in the estimation of the attributes and that avoids problems prominent with revealed preference data, such as multicollinearity and limited variation in key variables (Johnson et al., 2013; Lancsar et al., 2017).

Efficient design and orthogonal design are the two competing experimental design generation procedures. A design is orthogonal when the attribute levels of the different alternatives are uncorrelated in the choice sets (Louviere et al., 2000). In recent years, efficient design is becoming more prevalent as an alternative procedure with new algorithms to facilitate the design. Efficiency is a measure of the level of precision in which the parameter estimates on the attributes are measured (Johnson et al., 2013). Efficient designs have been empirically shown to lead to smaller standard errors in model estimation at smaller sample sizes compared to orthogonal designs (Rose and Bliemer, 2013). This is a distinct advantage for this study given the small sample size. The most commonly used efficiency measure is D-efficiency which leads to the smallest generalized variances of the parameter estimates (Louviere et al., 2008). For this study, during the design of a D-efficient DCE, the main considerations taken into account are; the number of blocks which comprise the total choice sets, the number of choice sets under each block, and the number of alternatives under each choice set.

A choice set with a large number of alternatives increases the cognitive burden on the respondents. A 3-alternative design is adopted in this study involving a choice between two hypothetical PES contracts and "neither of the two" (the status quo) option, which reflects the voluntary nature of farmers' participation in a PES scheme. This research applies the 'pick-one' format to better resemble real-life decision making. The number of choice sets that need to be included depends on the number of parameters to be estimated in the econometric model. In this study, there are 4 attributes and 8 household characteristics. Following the formula by Rose and Bliemer (2013), the required number of the choice sets for the DCE design are computed as; [$12/(3–1) = 6$]. Therefore, at least 6 choice sets should be presented to each respondent to generate the statistical minimum data points for the estimation of the parameters. This study went beyond the statistical minimum by setting 8 choice sets (see Table 2 for a sample choice set), after randomly dividing 16 choice sets into two blocks. After completing the DCE survey and excluding 6 sample households for incomplete responses in the choice experiment, the analysis is conducted based on a total of 4656 valid unlabelled discrete choices that are nested within 194 respondent farmers.

[3] *Timad* is a local land area measuring unit which is more familiar to farmers than hectare. In the study area, one *timad* is equivalent to 0.25 ha.

Table 2
Sample DCE choice set.

Attributes	Option 1	Option 2	Option 3
Number of planted trees	10	25	Neither of the two (the status quo)
Payment amount (monetary value)	125	155	
Payment type	Wheat[1]	Birr	
Duration of the contract	5 years	3 years	
Which option would you choose?	☐	☐	☐

[1] In option 1, the D-efficient design results in the payment amount of 125 ETB with a payment type in food (wheat) along with the other two attribute levels. The price for wheat during the survey period was 5 ETB per kg. Since the majority of the respondents are illiterate, we made the conversion of the monetary values into the actual amounts in the form of wheat (in option 1 for instance, we told farmers 125 ETB value of wheat means 25 kg).

4.4. Methods of data analysis

4.4.1. Empirical models specification

The analysis of DCE data relies on the framework provided by random utility theory where the choice problem is a problem of maximization of a utility function while the choices are observable indicators of utility. The conditional logit model (CLM), which is an extension of the multinomial logit model, developed by McFadden (1974) has been the workhorse econometric tool for analyzing discrete choice data. Accordingly, the utility that a farmer derives is given by Eq. (9) as:

$$Ui_{jt} = V_{ijt} + \varepsilon_{ijt};\ \ i = 1, 2, ..., N;\ \ j = 1, 2, ..., J;\ \ t = 1, 2, ..., T \tag{9}$$

where U_{ijt} is the unobservable, but true utility for farmer i derived from choosing alternative j in a choice set t. Relying on Eq. (8) in Section 3.2, V_{ijt} is the observable or systematic component of the overall utility of farmer i choosing alternative j in the choice set t, and εi_{jt} is the random component. The choice decision V_{ijt} is a function of the observable attributes of the alternatives in the choice sets and the observable characteristics of the respondent that do not vary across the choice sets. Hence, the specification for V_{ijt} is:

$$V_{ijt} = \alpha_j + X_{ijt}\beta + Z_i\delta \tag{10}$$

where X_{ijt} is a vector of observed attributes of alternative j and in choice set t, Z_i is the vector of socio-demographic characteristics of the farmer i, ε_{ijt} are disturbances assumed to be independently and identically distributed. α_j are alternative specific constants (ASCs) which represent a status quo intercept taking the value of 1 if farmers choose the status quo, and 0 otherwise. β is a vector of attribute-specific utility weights (homogenous across respondents), and δ is a vector of parameters to be estimated that are associated with household-specific characteristics

(Z_i). Plugging Eq. (10) into Eq. (9) leads to the following specification.

$$U_{ijt} = \alpha_j + X_{ijt}\beta + Z_i\delta + \varepsilon_{ijt} \tag{11}$$

where the elements in the specification of Eq. (11) are as described in Eq. (9) and Eq. (10). While CLM represents a natural starting point for estimating the parameters in Eq. (11), it imposes the unrealistic condition known as the independence of irrelevant alternatives (IIA), which states that the relative probabilities of two options being chosen are unaffected by the introduction or removal of other alternatives (Hausman and McFadden, 1984; Hensher and Greene, 2003). Hence, CLM cannot account for preference heterogeneity among respondents (or that their preferences depend only on observable characteristics). Moreover, CLM also restricts the percentage change in the probability for one alternative given a percentage change in the *m*th attribute of another alternative to remain the same (Hensher and Greene, 2003). If the IIA property is violated, CLM will result in biased parameter estimates.

In modeling individuals' choice, unobserved heterogeneity is pervasive and differential substitution patterns are likely to exist. The mixed logit (MIXL) model eliminates the limitations of the standard CLM by allowing the parameters in the model to vary across respondents. The basic structure of the specification under MIXL model remains identical to Eq. (11), but instead of β, a vector of individual-specific coefficients β_i is estimated (Hensher and Greene, 2003; McFadden and Train, 2000; Train, 2009). Such that $\beta_i = \beta + \eta_i$, where η_i is a random vector distributed MVN (0,Σ) and captures preference heterogeneity across respondents (Fiebig et al., 2010). However, a new strand of literature arise arguing that much of the preference heterogeneity may be better described as scale heterogeneity (SH) where β are fixed but the only variation between respondents is the scale of the idiosyncratic error term (Louviere et al., 2008). Building up from Eq. (11) after justifying scale heterogeneity as the source of variation in the attribute parameters, the estimation of β_i is $\beta_i = \sigma_i\beta$, where σ_i is a respondent-specific scale of the idiosyncratic error heterogeneity, distributed lognormal with standard deviation τ and mean $\overline{\sigma} + \delta Z_i$ (Fiebig et al., 2010).

To accommodate both preference and scale heterogeneity, (Fiebig et al., 2010) developed a generalized multinomial logit (G-MNL) model that provides an appealing and tractable way to describe both types of heterogeneity with a single equation as $\beta_i = \sigma_i\beta + \{\gamma + \sigma_i(1-\gamma)\}\eta_i$, where γ is a scalar parameter, and η_i and σ_i are as described above. Estimating G-MNL without imposing a constraint on γ allows more flexibility in how preference and scale heterogeneities are combined (Keane and Wasi, 2013). However, this will increase the required number of data points for the estimation (Lancsar et al., 2017). Since the sample size of this study is relatively small, we constrained $\gamma = 0$ resulting in the type II generalized multinomial logit model (G-MNL-II) (Fiebig et al., 2010), which is also known as scaled MIXL model (Greene and Hensher, 2010). Based on this model, the utility to farmer *i* from choosing alternative *j* in choice set *t* is given by:

$$U_{ijt} = \alpha_j + X_{ijt}\sigma_i(\beta + \eta_i) + Z_i\delta + \varepsilon_{ijt} \tag{12}$$

The G-MNL model in Eq. (12) nests CL, MIXL, and SH models. When $\sigma_i = 1$ and $\mathrm{var}(\eta_i) = 0$, the G-MNL specification revert back to CLM. When $\sigma_i = 1$, the estimation will be MIXL model. When $\mathrm{var}(\eta_i) = 0$, the specification becomes the SH model. Moreover, in the estimation stage, the attributes (X_{ijt}) could be allowed to freely correlate with each other.

The latent class conditional logit (LCL) model was also employed to account for heterogeneity in preferences of groups of farmers. In LCL, farmers are sorted into a discrete number of latent classes (C) and distinctive taste parameters are estimated for each class, $\beta = (\beta_1, \ldots, \beta_c)$, which are heterogeneous across classes but homogeneous within a class (Boxall and Adamowicz, 2002). Following Greene and Hensher (2003), the LCL model is specified in Eq. (13) by taking a logit model as the central behavioral model where the choice probability that a farmer *i* (*i* = *1*, … , *N*) of class c chooses alternative *j* (*j* = *1*, … , J) from choice set *t* (*t* = *1*, … , T) as:

$$\Pr(choice_{it}=j|class=c) = \Pr_{it|c} = \frac{\exp(\beta_c' x_{itj})}{\sum_{k=1}^{J}\exp(\beta_c' x_{itk})}\, c = 1,\ \ldots,\ C \tag{13}$$

where β_c' is a vector of class-specific utility parameters associated with the vector of attributes x_{itj}. Given the class membership status is unknown, the unconditional likelihood of choices of farmer *i* needs to be specified. Following Pacifico and Yoo (2013), the sample log-likelihood is then obtained by summing each respondent's log unconditional likelihood as shown in Eq. (14).

$$\ln L(\beta,\theta) = \sum_{i=1}^{N}\ln\sum_{c=1}^{C}\pi_{ic}(\theta)\prod_{t=1}^{T}\Pr_{it|c} \tag{14}$$

where $\pi_{ic}(\theta)$ is the weight for class *c*. β and θ can be more conveniently estimated via a well-known Expectation-Maximization (EM) algorithm for likelihood maximization in the absence of information on each agent's class membership status (Pacifico and Yoo, 2013). An issue to be noted is the choice of the number of classes. To decide the optimal number of classes, we used the value of C that minimizes the measures of variants of information criteria methods (Louviere et al., 2000).

4.4.2. Estimating marginal willingness to accept

The WTA measure for an attribute corresponds to a compensatory payment that farmers, on average, would be willing to accept to make a one-unit improvement in the attribute level (or to adopt a category of an attribute) in the case of negative values and to give up in the case of positive values. WTA measures on the attributes provide a convenient way for comparing the marginal utility weights that respondents assign to the attributes. Calculating WTA measures could follow estimation either in the preference space or in the WTA space. In the former, a distribution of coefficients in the utility function is specified and then a distribution of the WTA is later derived. This study follows the standard approach which assumes that attribute coefficients are normally distributed and the payment coefficient is fixed to compute the WTA as the ratio of the coefficients for non-payment attributes (β_A) to the negative of the payment attribute coefficient (β_P), such that:

$$WTA_A = \frac{\beta_A}{-\beta_P} \tag{15}$$

The main problem with fixing the distribution of the payment coefficient while estimating the WTA in the preference space (Eq. (15)) is that all individuals are assumed to have the same marginal utility of income (Meijer and Rouwendal, 2006), and variation in scale would be erroneously translated into variation in WTA resulting in untenably large WTA measures (Train and Weeks, 2005). To solve the problem of artifact measures, Train and Weeks (2005) recommend computing reasonable WTA estimates directly in the WTA space as presented in Eq. (16). Accordingly, we applied maximum simulated likelihood after reformulating the model in such a way that the distributional assumptions are made directly on the WTA measures.

$$U_{ijt} = \lambda_i(-P_{ijt} + \gamma_i x_{ijt}) + \varepsilon_{ijt} \tag{16}$$

where U_{ijt} is as described under Eq. (9), P_{ijt} is the payment attribute, x_{ijt} is non-payment attributes, $\lambda_i = \beta_{Pi}/\sigma_i$, $\gamma_i = c_i/\lambda_i$, $c_i = \beta_{Ai}/\sigma_i$ and ε_{ijt} is the disturbance term distributed with variance given by $\sigma_i^2(\pi^2/6)$. σ is scale of the idiosyncratic error heterogeneity. β_A is a vector of parameter estimates of non-payment attributes to be estimated on WTA space.

5. Results

5.1. Descriptive statistics

This study hypothesizes that the household characteristics, particularly those (closely) related to farmers' perception on climate-smart agroforestry, income or wealth, and access to information can influence

Table 3
Household level characteristics.

Household characteristics	Coding	Percent	Mean	SD
Sex of the head	1 if Male; 0 otherwise	73		
Age of the head	Number of years		48.59	14.15
Family size	Number of household members		5.76	2.29
Landholding	Total land size in hectare		0.92	0.94
Education status	1 if read and write; 0 otherwise	37		
Extension contact	1 if Yes; 0 otherwise	77		
Iddir membership	1 if Yes; 0 otherwise	61		
Owns television or radio	1 if Yes; 0 otherwise	35		

Note: SD stands for Standard Deviation.

their preferences to participate in a PES program that promotes fertilizer tree planting (see Section 3.2). Table 3 presents the household level variables that are included in the analyses. Namely, these variables are: gender, age, and educational status of the household head; family size; total land holding; access to agricultural extension services; membership to informal information sharing and self-help farmer groups (*iddir*); and ownership of television or radio.

The means and standard deviations for the continuous variables and the proportion of households with responses equal to 1 for the binary variables are reported in Table 3. Given that the household characteristics do not differ between each choice set, they were entered into the regression models through interactions with the alternative specific constants (status quo intercepts). Including these effects in the analysis minimizes biases that would otherwise arise in the parameter estimates of the main effects (the attributes).

Out of our sample 200 farmers that faced 8 choice-sets each involving a choice between two alternative PES contract options and the status quo (see Table 2 for a sample choice set), we collected complete responses on 194 farmers. Around 11 percent of the respondents (22 farmers) consistently opt against PES program regardless of the varying attributes in the alternatives of the PES options and prefer the status quo (mono-cropping farming system) in all their choices. Such a choice behavior could be best explained by a bias towards the status quo (Dean et al., 2017; Samuelson and Zeckhauser, 1988) which prevents farmers from adopting climate-smart agroforestry. However, around 89 percent of the respondents supported the PES program depending on the contract attributes in the choice sets. This high level of preference towards the PES contract implies that the choice sets offer plausible and salient options to incentivize farmers to practice climate-smart agroforestry. Table 4 reports mean difference tests on household characteristics based on whether respondent farmers consistently opt against PES contract (i.e. choose only the status quo) for the entire choice sets.[4] The averages show that sample households who consistently choose the status quo are more likely to be female-headed, have smaller family size, and are less likely to own TV or radio.

5.2. Generalized multinomial logit model results – farmer-specific preference heterogeneities

Columns 1 and 2 in Table 5 present the parameter estimates for the choice analysis under G-MNL uncorrelated and G-MNL correlated models, respectively.[5] The parameter estimates from the uncorrelated G-MNL (column 1) are used as starting values for the final G-MNL correlated model. Post estimations following the correlated models offers insight on preference heterogeneity, which is estimated as the deviations from the mean utility weights attached to the attributes. Since the observations in the choice experiment are not independent, all standard errors are cluster-robust at the household level.

For brevity, only the results from the correlated G-MNL model are discussed. There are two main reasons for making this choice. First, in addition to the significant presence of preference heterogeneity (i.e.,

Table 4
Mean differences in household characteristics based on choice behavior.

Household characteristics	Choice decision (in favor of)		Mean difference
	PES contract (at least once)	No-PES contract (always the status quo)	
Sex of the head	0.75	0.55	0.20**
Age of the head	48.20	51.64	−3.44
Family size	5.94	4.37	1.57***
Landholding	0.95	0.72	0.23
Education status	0.38	0.32	0.06
Extension contact	0.78	0.68	0.10
Iddir membership	0.63	0.46	0.17
Owns television or radio	0.38	0.14	0.24**

** $p < 0.05$.
*** $p < 0.01$.

Table 5
Parameter estimates of the G-MNL model.

	(1) Uncorrelated G-MNL		(2) Correlated G-MNL	
Variables	Mean	SD	Mean	SD
Payment amount	0.0154** (0.0074)		0.0138*** (0.0045)	
Number of trees	−0.0512** (0.0215)	0.1346*** (0.0443)	−0.0408** (0.0171)	0.1846*** (0.0306)
Payment in food	3.5627* (1.8278)	6.9466** (2.8442)	1.8846*** (0.4394)	5.7263*** (0.9500)
Contract period	−0.2263* (0.1294)	0.9517*** (0.3568)	−0.1367** (0.0580)	0.5980*** (0.1122)
Taw (τ)	−0.7263** (0.3092)		−0.5875*** (0.1407)	
ASC	−0.7616 (3.9333)		0.4801 (5.5422)	
ASCXAge	0.0724 (0.0593)		0.0440 (0.0914)	
ASCXSex	−3.2760* (1.7773)		−2.8743 (4.7451)	
ASCXEducation	1.8962 (1.6168)		1.0666 (2.6228)	
ASCXFamily size	−0.2509 (0.2111)		−0.2987 (0.5717)	
ASCXLandholding	−1.1483* (0.6815)		−1.3111** (0.6570)	
ASCXExtension contact	0.7441 (1.1498)		0.6704 (2.1210)	
ASCXTvoradio	−4.5662** (2.2929)		−4.1057* (2.2389)	
ASCX*Iddir* member	−3.0362** (1.2859)		−2.8475 (1.9463)	
Observations	4656		4656	
AIC	1702.64		1662.07	
BIC	1812.22		1790.99	
Log-likelihood	−834.32		−811.04	

Note: Robust standard errors in parenthesis
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
The standard deviations (SD) on the attributes capture preference heterogeneity across farmers.

[4] We thank the anonymous reviewers for pointing out that it would be informative to assess whether respondents who consistently opted out of the PES program have any different household characteristics.

[5] The coefficients on the attributes, intercept and its interaction with household characteristics are estimated under the specification of Eq. (12) using Stata 15. The G-MNL model was estimated via simulated maximum likelihood using the user-written Stata commands developed by Gu et al. (2013).

the statistically significant standard deviations around the mean utility weights on the attributes), the standard deviation of the respondent-specific scale of the idiosyncratic error heterogeneity (τ) is highly significant. These results signal the presence of preference and scale heterogeneities, and hence the G-MNL model is more appropriate than MIXL model (parameter estimates are shown in Appendix Table A.1) as it accounts for both types of heterogeneity. Second, goodness-of-fit tests using log-likelihood (LL), Akaike information criteria (AIC) and Bayesian information criteria (BIC) show that the correlated G-MNL had the best fit for the data than the uncorrelated G-MNL.

Table 5 column 2 shows that the coefficients on all attributes are statistically significant, an indication of their relevance to the PES program. As expected, the attribute "payment amount" has a positive coefficient, an indication that farmers derive higher utility from higher payment amounts. Farmers also demonstrate strong preferences for food as a mode of payment than cash. Intuitively, cash might be thought to dominate farmers' choice since payments in cash give more flexibility and expand the array expenditure choices. However, one should closely scrutinize the contextual environment where farmers are making their choices. The failure of output markets could explain farmers' preference towards payment in food rather than in cash. The study area is characterized by its vulnerability to climate shocks and the associated severe food shortage (Gebrehiwot and Veen, 2013). In the absence of well-functioning markets that mobilize food items from surplus to deficit areas, cash transfers are vulnerable to price increases of food items thereby eroding the purchasing power of the transfers (Sabates-Wheeler and Devereux, 2010). Therefore, farmers would rationally choose the end good (food) rather than the means (cash). Similar preference to receive food over cash was also observed among the participants of a national safety net program (PSNP) in Ethiopia (Devereux et al., 2006; Wiseman et al., 2010) because cash transfers are not regularly adjusted to inflation rates (Baye et al., 2014).

The coefficients of "number of trees" and "contract period" are negative indicating that, on average, farmers strongly prefer low numbers of required planted trees and short-term contract periods. These attributes positively influence farmers' decisions to take-up contractual tree planting practice. Loss aversion may prevent farmers from adopting innovations with unknown returns (Fafchamps, 2009). Since climate-smart agroforestry is not a common practice in the study area, loss aversion is a plausible explanation for farmers' reluctance to fully commit their land and time to plant and maintain *faidherbia albida* trees. Further analysis shows that except for the correlation between payment in food and contract period, the non-diagonal terms in the covariance matrix of the attributes are positive and statistically significant (Table A.2 in the Appendix). Preference towards planting more trees is positively and significantly associated with their preference for food payments. Similarly, there is a positive and significant correlation between the number of planted trees and contract period.

Turning to the interactions between household-level characteristics and the ASC (choosing the status quo over PES options), the results show that farmers with larger landholdings and those who own televisions or radios strongly prefer the PES contract over the status quo. The positive and significant effect of landholding on farmers' choice to enroll in a PES program is well documented in recent studies by Bremer et al. (2014) in Ecuador and Lansing (2017) in Costa Rica.[6] Landholding is a key determinant of the household's farm income generating capacity and a good proxy for the households' wealth especially in agrarian economies (Alesina and Rodrik, 1994). Consequently, farm income and wealth are highly correlated with risk-taking behavior and patience of the households (Tanaka et al., 2010). Hence, farmers with larger landholdings are more willing to accept new practices with future gains. There are two plausible explanations on the significant effect of ownership of television or radio on farmers' participation in the PES program. One is acquiring these durable assets can also signal the households' wealth, and hence the above discussion still holds. The other possible explanation is that as ownership of information media these channels may determine access to information that could positively shape farmers' knowledge and attitudes towards climate-smart agroforestry and therefore affect their willingness to accept the PES program. However, we are not aware of any national or local TV or radio program specifically designed to promote agroforestry. Hence, further research in this direction may reveal the practicality of our suggestive explanation. Other demographic and socio-economic variables are not statistically significant predictors. For the variables sex of the head and family size of the households, we observed statistically significant mean differences between households who consistently opt against the PES scheme and the remaining households (Table 4). After conditioning on other household characteristics, the variations cease to exist under our preferred model (Table 5 column(2)).

5.3. Willingness to accept measures

The WTA estimates – estimates of the marginal utility of receiving payment – under both the preference and WTA spaces are presented in Table 6. However, for the reasons presented in Section 4.4.2, we only offer interpretations based on the WTA measures that are estimated in the WTA space.[7] Farmers are willing to receive around 59 ETB (2.60 USD) less in annual payment per *timad*, which is 0.25 hectare (ha) of land, if the mode of payment is food rather than cash. Farmers are willing to accept 1 ETB per *timad* (0.18 USD per ha) per year if they have to plant an additional *faidherbia albida* tree on their farm plot. Farmers are also willing to accept additional annual payment that worth around 2 ETB per *timad* (0.35 USD per ha) for an increase in the PES contract by a year.

5.4. Further insights from the latent class conditional logit model - class-specific preference heterogeneities

The results from the LCL model offer insight into the variations in the preferences across different segments of farmers by allowing the attribute coefficients to vary across the (latent) classes.[8] The selection of the optimal number of latent classes was based on consistent Akaike Information Criteria (CAIC) and BIC, which are more critical toward models with more parameters by using penalty functions that increase in the number of respondents. As shown in Table 7, CAIC and BIC are at their lowest for five classes – types of farmers with different preferences for PES contract attributes. The household characteristics (described in Table 3) are used for predicting class membership to separate respondents with different preferences for the attributes.

Table 8 reports the regression coefficients of the LCL model using 5 latent classes. The heterogeneity of preferences is reflected in the different parameter estimates for the attributes across the segments. The mean (over respondents) highest posterior probability of class membership is about 0.95, which indicates that the model adequately differentiates the underlying heterogeneity in preferences for the observed choice behavior. While class 3 has the highest average membership probability of 38%, class 5 has the lowest (12%).

Given that there are 3 alternatives in a given choice set, the (un) conditional probability of actual choice examines the model's ability to make in-sample predictions of the actual choice outcomes (without) conditioning on being in a given class c. The LCL model describes the

[6] It should be noted that, especially in the context of landholding, farmers in Latin America and sub-Saharan Africa countries are quite distinct. Smallholder farming on less than 2 ha of land is the major livelihood activity of rural households in SSA in general and in Ethiopia in particular.

[7] This study used a Stata code developed by Hole (2016).

[8] The estimation is based on the Stata code developed by Pacifico and Yoo (2013).

Table 6
Willingness to accept measures in the preference and WTA space.

Attributes	Preference space[1] Correlated G-MNL (in ETB)	WTA space (in ETB)
Number of Trees	2.9494	0.9924*** (0.1735)
Payment in food	−136.3085	−58.8229*** (2.3842)
Contract period	9.8840	1.8401*** (0.5493)

Note: Robust standard errors in parenthesis. *** $p < 0.01$.
1 ETB is 0.044 USD based on the survey period average official exchange rate.
[1] The ratio of the attribute coefficient to the negative of the coefficient for the "payment amount" attribute from Table (5) column (2).

Table 7
Selection criteria for an optimal number of latent classes.

Classes	LLF	Number of parameters	CAIC	BIC
2	−1042.447	17	2191.88	2147.88
3	−830.6701	30	1850.139	1820.139
4	−786.1932	43	1842.999	1799.999
5	−743.2836	56	1838.992	1782.992
6	−730.5301	69	1895.298	1826.298

average predicted probability of actual choice after conditioning on respondents' membership probability. For instance, the class 5 average unconditional probability of choosing the actual alternative was 24%, whereas this likelihood increased to 80% conditional on membership probability.

Respondents in class 1 have statistically significant coefficients for all the attributes, indicating that farmers in this segment care about all of the PES program design features. Class 2 consists of a group of farmers that derive higher utility from a PES program with a higher payment amount and longer contract period. In this class, the respondents' utility weights attached to the number of planted trees and payment in food are not statistically different from zero. Respondents in class 3 exhibit strong preferences for a higher amount of payment in the form of food (wheat). Class 4 comprises farmers whose preferences are the exact opposite of those in class 3. Respondents in class 4 derive higher utility by receiving a high amount of payment in the form of cash.

Unlike the previous 4 classes, the payment amount coefficient for respondents in class 5 is negative and significant at 1% probability level. The coefficients for the remaining attributes in this class are not statistically different from zero. This indicates that farmers in class 5 are strongly against receiving payments from the PES program. Even though there is no theory-based explanation for this result, an incident that had occurred in the study area involving farming households and

Table 8
Class-specific attribute coefficients in LCL model.

Attributes	Class 1	Class2	Class3	Class4	Class5
Payment amount	0.0354***	0.0103***	0.0198**	0.0228***	−0.0339***
	(0.0051)	(0.0026)	(0.0091)	(0.0030)	(0.0105)
Number of trees	−0.1252***	0.0204	0.0087	0.0157	0.0079
	(0.0262)	(0.0130)	(0.0254)	(0.0162)	(0.0620)
Payment in food	0.8887***	0.2020	4.5637***	−1.9433***	1.1645
	(0.2871)	(0.1924)	(0.6538)	(0.2507)	(1.1598)
Contract period	−0.3160***	0.2146***	−0.1938	−0.0025	−0.0979
	(0.0695)	(0.0448)	(0.1385)	(0.0417)	(0.1891)
Class share	0.15	0.18	0.38	0.17	0.12
Unconditional prb.	0.50	0.47	0.60	0.37	0.24
Conditional prb.	0.65	0.60	0.96	0.72	0.80

Standard errors in parenthesis *** $p < 0.01$, ** $p < 0.05$.

observed choice behavior in each class with a significantly higher

Table 9
Variations in household characteristics between classes of farmers.

Household characteristics	Class 1	Class 2	Class 3	Class 4	Class 5
Age	0.0009	−0.0138	−0.0141	−0.0011	Fixed
	(0.0232)	(0.0229)	(0.0181)	(0.0225)	parameter
Sex	1.1969	1.2743	0.6186	−0.1737	Fixed
	(0.9141)	(0.8227)	(0.6698)	(0.7935)	parameter
Education	−0.3733	−1.6915**	−0.4958	0.3218	Fixed
	(0.7488)	(0.8304)	(0.6206)	(0.7210)	parameter
Family size	0.1343	−0.0105	0.2196	0.3303*	Fixed
	(0.1779)	(0.1642)	(0.1415)	(0.1754)	parameter
Total land	0.3764	0.8804*	0.0719	−0.9940	Fixed
	(0.4218)	(0.4550)	(0.4058)	(0.7442)	parameter
Extension contact	−0.2132	18.4000	−0.4262	−0.5110	Fixed
	(0.7989)	(311.567)	(0.6079)	(0.7292)	parameter
Owns tv/radio	0.5791	1.1834	1.3811*	1.8657**	Fixed
	(0.8796)	(0.8048)	(0.7156)	(0.7936)	parameter
Iddir membership	1.9776***	0.8824	0.8516	−0.2513	Fixed
	(0.7554)	(0.6531)	(0.5214)	(0.6290)	parameter
Constant	−2.8091*	−18.9334	−0.1010	−0.7946	Fixed
	(1.6813)	(311.5671)	(1.1843)	(1.4221)	parameter

Standard errors in parenthesis
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

coordinators of a cash transfer pilot program may provide a behavioral explanation. In 2011, UNICEF Ethiopia launched a cash transfer pilot program in Hintalo Wajirat district also targeting our sample *tabias*. However, some households wrongly perceived that they were deliberately targeted based on their religion and were being offered money to change their faith. The implementation of the program was only realized after awareness meetings with the households to explain the real intention of the cash transfers. Based on personal communication with the cash transfer coordinator officer in the study area, the issue had sporadically arisen until the official completion of the pilot program in 2014. Despite explaining the purpose of the PES payments in the 'cheap talk' script of the DCE survey (stated under Appendix Fig. 2), our finding may also point to the presence of a segment of farmers that strongly oppose any payments with monetary value because of persistent misconceptions on the intentions of the payments.[9] The mean and covariance of the attribute estimates after the LCL model are shown in Appendix Table A.3.

Further analyses on variations in household characteristics of farmers in the various classes are shown in Table 9. The household characteristics across the segments of farmers are compared using the

[9] We do not have prior knowledge about the incident during the survey or data analysis. We learn about it while trying to provide a possible explanation for the observed result.

5th class as a base category, where the household characteristics are normalized to 0 for identification. Hence, we can compare the household characteristics of farmers in class 5 with farmers in the remaining classes who have demonstrated a strong common desire towards higher up-front payments. Accordingly, as measured by their membership to an informal self-help farmer groups (*iddir*), farmers in class 5 are worse-off in terms of their social capital than those in class 1. Farmers in class 5 have smaller landholdings but are more likely to be able to read and write than households in class 2. Class 5 also comprises farmers that are less likely to own TV or radio than those in class 3 and class 4. Moreover, farmers in class 5 have smaller family size than farmers in class 4.

6. Discussion

While conventional PES schemes reward agroforestry in developing countries, the payments are made only after farmers provide the outputs (grown-up trees) that render ecosystem services. In the analogy of conditional cash transfers, for example, assuming that households are eligible for social assistance for their children schooling, the timing of the transfers in a conventional PES design may mean poor and vulnerable households would only receive the transfers after their children graduate from high school or college. On the contrary, the design of our hypothetical PES scheme resembles an equity-oriented conditional cash transfer in exchange for the initial farmers' decision to plant fertilizer trees (*faidherbia albida*) within their agricultural land. In this respect, our PES design takes into account the fact that farmers in SSA are highly financially constrained (Karlan et al., 2014) which makes them reluctant to invest in agricultural practices that do not result in immediate cash inflows (Neufeldt et al., 2011). Respondent farmers in our study exhibit a strong preference for the up-front PES payments in the form of food. They also prefer higher annual payments for a few years than small amounts that are made for many years.

Therefore, changing the timing of payment in a PES program may trigger a change in behavior among farmers in SSA in favor of climate-smart agroforestry, which has economic and ecosystem benefits. If a PES program compensates farmers for the investment costs associated with adopting climate-smart agroforestry at the initial years, when cash outflows characterize the investment, farmers are willing to engage in an environmentally conscious land use (planting trees) and there is a high possibility for large-scale adoption of the innovation across the landscapes of SSA. The current adoption rate in semi-arid and sub-humid Ethiopia is 26 percent (Iiyama et al., 2017). Based on the design features of our study's PES scheme, almost 90 percent of sample respondents welcome the idea of adopting the innovation.

It is also important to take into account that attributes of PES schemes are not equally weighted by different segments of farmers that are classified based on variations in their choice decisions and household characteristics. We observe that there is a class of farmers that are firmly against receiving payments from a PES program. Moreover, farmers in different classes also assign different utility weights to the non-payment attributes. In general, our understanding of the household and community contexts that farmers are operating and making decisions is vital to develop outreach strategies for successful implementation of agri-environmental policies such as PES interventions.

Income and wealth have been significant household characteristics that influence households participation in a PES scheme (Bremer et al., 2014; Lansing, 2017). Even in the context of smallholder farmers that are characterized to operate on average landholding of smaller than 2 ha (Lowder et al., 2016) variables such as landholding and ownership of durable assets that can proxy the households' income and wealth significantly affects their willingness to participate in a contractual agroforestry practice under a PES scheme.

7. Concluding remarks

A DCE survey, which is constructed using a D-efficient design procedure, was conducted on 200 smallholder farmers in Ethiopia to estimate the utility weights they assign on various design features of a hypothetical PES program that promotes the planting of fertilizer trees on their agricultural land. The use of the G-MNL and LCL models allow for farmer- and class-specific preferences, respectively. The results from G-MNL model show that farmers derive higher utility from higher amounts of up-front payments. Moreover, farmers prefer a PES program that uses food (wheat) as payment, requires a low number of planted trees and has a shorter contract period. Farmers are willing to receive lower annual payments if the payments are in food rather than cash. Conversely, farmers demand extra annual payments for the planting of an additional fertilizer tree and extension of the PES contract by a year. The results from LCL model show the presence of heterogeneity in preferences across segments of farmers in conjunction with differences in household characteristics.

The study also finds that households' landholding and ownership of a television or radio – which can serve as proxies for income and wealth – positively influences their preference for the PES program. Ownership of TV or radio may also proxy households' access to information media. Hence, the other suggestive explanation is that the mass media may serve as channels for raising community awareness on climate-smart agroforestry. Further research in this direction may reveal the practicality of our suggestive explanation. The lack of effect of agricultural extension services on farmers' choice behavior is a red flag regarding the emphasis given to agroforestry in the regional extension package. There is, therefore, need to further investigate how fertilizer trees are promoted by the extension service and if methods of promotion are effective and need to be changed.

The study is a novel contribution to the PES literature as the design of the PES program features payments starting from the initial year, as opposed to conventional PES programs that pay after the ecosystem services are realized. The study's payment arrangement is suitable for poor and vulnerable smallholder farmers as it rewards an environmentally conscious land use (planting trees) that has delayed economic and ecosystem benefits. The results shed light on the design considerations that must be taken into account for integrating efficiency and equity objectives in PES programs that accommodate agroforestry in the context of smallholder farming systems in SSA. The study reveals the presence of farmer- and class-specific heterogeneous preferences on the design features of the PES scheme. Hence, practitioners and policy makers should develop strategies to increase outreach beyond the average farmer to achieve successful implementation of environmental policies that promote the large-scale uptake of climate-smart agricultural innovations. Future field experiments based on the design features of our DCE study will show the practicality of our findings.

8. Disclosure

We declare that this article is our bona fide work and is not submitted for publication elsewhere.

Declaration of Competing Interest

None.

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Appendix

Table A.1
Parameter estimates of the MIXL model.

	(1) Uncorrelated MIXL		(2) Correlated MIXL	
Variables	Mean	SD	Mean	SD
Payment amount	0.0093***		0.0094***	
	(0.0034)		(0.0030)	
Number of trees	−0.0378***	0.0992***	−0.0278*	0.1466***
	(0.0136)	(0.0143)	(0.0142)	(0.0228)
Payment in food	2.0757***	4.7647***	1.5569***	4.5633***
	(0.4015)	(0.6178)	(0.4228)	(0.5832)
Contract period	−0.1416***	0.6044***	−0.0986**	0.4712***
	(0.0453)	(0.0799)	(0.0497)	(0.0647)
ASC	−0.2541		0.4231	
	(2.1726)		(2.7845)	
ASCXAge	0.0415		0.0270	
	(0.0308)		(0.0394)	
ASCXSex	−2.0110**		−1.9021	
	(1.0088)		(1.9938)	
ASCXEducation	1.2148		0.8108	
	(0.8932)		(1.3499)	
ASCXFamily size	−0.1974		−0.2762	
	(0.1822)		(0.3130)	
ASCXLandholding	−0.7352		−0.7635	
	(0.4751)		(0.4828)	
ASCXExtension contact	0.4549		0.3852	
	(0.8664)		(1.0697)	
ASCXTvoradio	−2.9163***		−2.9163**	
	(0.9070)		(1.2075)	
ASCXIddir member	−2.0365***		−2.3367**	
	(0.7331)		(0.9244)	
	(1) Uncorrelated MIXL		(2) Correlated MIXL	
Observations	4656		4656	
AIC	1704.95		1666.85	
BIC	1808.09		1789.32	
Log likelihood	−836.48		−814.43	

Note: Robust standard errors in parenthesis
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
The standard deviations (SD) on the attributes – preference heterogeneity across farmers.
The MIXL model was estimated via simulated maximum likelihood using the user-written Stata commands developed by Hole (2007).

Table A.2
Variance-covariance matrix of the attribute coefficients in the correlated G-MNL model.

Coefficients	Number of trees	Payment in food	Contract period
Number of trees	0.0341***		
	(0.0113)		
Payment in food	0.5899***	32.7907***	
	(0.1968)	(10.8806)	
Contract period	0.0883***	0.7869	0.3576***
	(0.0319)	(0.6979)	(0.1342)

Standard errors in parenthesis *** $p < 0.01$.

Table A.3
Preference heterogeneity described by mean and covariance of attributes after LCL model.

Coefficients		Payment amount	Number of trees	Payment in food	Contract period
	Mean	0.0143	−0.0086	1.7460	−0.0977
Covariance	Payment amount	0.0004			
	Number of trees	−0.0004	0.0025		
	Payment in food	0.0026	0.0101	5.8699	
	Contract period	−0.0010	0.0052	−0.2190	0.0295

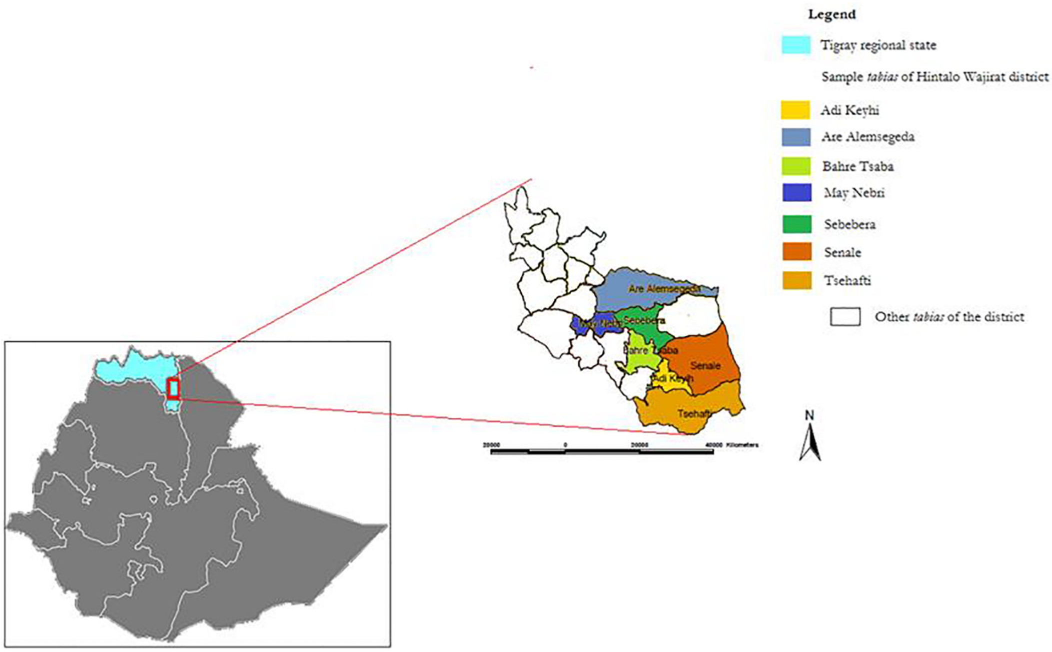

Fig. 1. Map of the study area.

(a) (b)

Fig. 2. Photos of climate-smart agroforestry presented to all sample respondents. (a) Faidherbia albida trees on agricultural land before sowing annual crops (Photo: A. Agard). (b) Faidherbia albida trees intercropped with annual crops (Photo: Hadgu).

Note: The following "cheap talk" script was read to all sample farmers while presenting the above photos.

Now you are kindly requested to make choices between three alternatives. Suppose you are facing production decisions involving two alternatives where you would be incentivized (in-cash or in-kind) for planting faidherbia albida trees on your agricultural land and a third alternative with an option to choose the status quo (an alternative that you can say "I do not want to plant trees in my farm plots"). There are no "correct" or "wrong" choices but you have to make priorities among the three alternatives and make only one choice in each choice set. Please be honest and reflect your choice as if it would be implemented right now for real, i.e. either you would plant the number of faidherbia albida tree seedlings within your agricultural land in exchange for annual payments (in-cash or in-kind) that will be made for a given number of years as specified in your choice or you would not plant the trees.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecoser.2019.100964.

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